A conceptual framework for business intelligence critical success factors

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A conceptual framework for business intelligence critical success factors

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Abstract: From theoretical and practical viewpoints, business intelligence application is considered by scholars and managers in their organisations. Most organisations are seeking to develop their capabilities and to gain a sustainable competitive advantage through business intelligence. Previous studies are mostly descriptive and they have emphasised the importance of business intelligence. This study aims to provide a conceptual framework for the assessment of business intelligence critical success factors in the organisations. The study was a pure research, which was conducted based on scientific research method and a five-year application of business intelligence in different organisations. The scale validity was approved using confirmatory factor analysis. The statistical data was also collected from 78 large and medium-sized companies. In this study, consistent with scientific research method principles, an operational scale is presented for the implementation of business intelligence. The results indicate that a suitable software and hardware platform is one of the most significant technical infrastructures for business intelligence implementation.

Keywords: business intelligence; BI; software maturity; data integrity; hardware maturity; data transparency.

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1 Introduction

In today's increasingly complex business environment, organisations require special management information systems for quick response to the market variations. These information systems must be able to perform a variety of causal analyses of the organisation and its environment (Rubin and Rubin, 2013; Aufaure et al., 2015). In the mid-90s, 'business intelligence' (BI) emerged prominently in response to the remarkable changes of the competitive environment, the rapid growth of technology, increasing IT support for the implementation of the business process, and worldwide diffusion of the internet (Anandarajan et al., 2004; Cheung and Li, 2012). BI rooted in decision support system (DSS) has undergone a significant development over the last decades and today it is one of the areas of DSS that attracts a great deal of interest from both academia and industries (Negash, 2004; Arnott and Pervan, 2008; Wang, 2016). BI is a type of information system that can be used for supporting complex decision-makings and solving semi-structured problems (Shim et al., 2002; Turban et al., 2011; Martin and Buxmann, 2015).

Organisations have implemented BI applications to realise a variety of organisational benefits and they have invested considerable resources in the usage of BI systems (Yoon et al., 2017; Nofal and Yusof, 2016). BI helps corporate managers and decision makers to make relevant, accurate, timely, and smart decisions and thus it leads to enhance organisational productivity and profitability (Watson, 2005; Ranjan, 2008). Managers are able to relate their long-term and strategic goals to short-term and operational goals using BI (Schulz et al., 2015; Wang, 2016). The objective of BI system implementations is to improve main activities' performance, to support information quality and timeliness, to empower managers to be better aware of their company's position compared to competitors, and to support the organisational decisions by providing access to the existing data (Williams and Williams, 2007; Davenport, 2010). It might be presented as an architecture, tool, technology or system that helps data gathering and storage, analyses it through analytical tools, facilities reporting, querying and delivers information or

knowledge to improve organisational decision-makings (Thierauf, 2001; Negash, 2004; Turban et al., 2008). By providing access to data, modern BI consists of various tools, applications, processes, databases, and architectures for all levels of an organisation (Turban et al., 2011). BI systems are implemented to provide analytical capability to offer suggestions for improving operational or strategic processes or product characteristics (Williams and Williams, 2007; Howson, 2007).

Most organisations still experience a lack of BI in their decision-making processes when implementing enterprise systems (Rouhani and Ravasan, 2015). BI assessment in enterprise systems before buying and developing them is a critical issue for managers (Elbashir et al., 2008; Rouhani et al., 2012). Although many scholars and practitioners have considered BI systems as a source of improved decision-making capabilities, limited efforts have been made for BI assessment (Chou et al., 2005; Arnott and Pervan, 2008; Hou and Papamichail, 2010). BI system implementation in an organisation is not possible without examining its infrastructure and thus it may not improve the efficiency. Therefore, it is essential to explain and define BI critical success factors (CSFs). In other words, BI as a new paradigm of organisation and management should be further developed, i.e., the key aspects of BI must be identified and operationalised. In fact, BI as an emerging discipline requires developing more theoretically. This is no time to be recommended that organisations have achieved market success through BI because they are familiar with the importance of BI. Their main problem is successful BI implementation. Therefore, in this study, first, the relevant research literature on the emergence and importance of BI is discussed. Then, the key aspects of BI implementation are introduced. Next, the developed framework is validated using proper statistical techniques. Finally, results and discussion will be provided.

2 Theoretical framework and literature review

In the early decades of the twenty-first century, BI has been introduced as a top priority of information systems and online analytical processing (OLAP) technology. However, for the first time, BI has replaced other terms such as executive information systems and managerial information systems (Thomsen, 2003; Negash, 2004; Turban et al., 2008). There are various definitions of BI in scientific and technical literature. Some studies have broadly defined BI as a holistic and sophisticated approach to DSS (Moss and Atre, 2003; Alter, 2004; Mikroyannidis and Theodoulidis, 2010). Others have discussed it from a more technical approach; they have considered BI as a strategic information system capable of providing applied information through a centralised database, originated from numerous sources, transformed into meaningful information via BI analytical tools to facilitate business insights leading to informed decisions (Kulkarni et al., 2007; Turban et al., 2008). In other studies, BI has been defined as a method for improving business performance by providing organisational decision makers with actionable information. This definition itself leads to fundamental concepts such as data warehouse (DW), data mining (DM) and data sovereignty (Ranjan, 2008; Schulz et al., 2015).

BI is also defined as a collection of integrated operational and decision support applications and databases that provide the businesses with easy access to business data. Therefore, BI systems can be viewed as the next generation of DSSs (Arnott and Pervan, 2008). Through dashboards that display key performance indicators, and display current

or historical data relative to organisational or individual targets on scorecards, BI systems are able to provide real-time information, create rich and precisely targeted analytics, and manage business processes (Mwilu et al., 2015). BI integrates data, which is stored and aggregated by the organisation. Therefore, it is based on usable facts to help make accurate and efficient decisions.

Based on the traditional approach to BI for improving the efficiency of decision-making, BI identifies various technical tools and provides reports and forecasts. BI technical tools include DW, extract-transform and load (ETL), OLAP, DM, text mining, web mining, data visualisation, geographic information systems (GIS) and web portals (Kudyba and Hoptroff, 2001; Raisinghani, 2004; Khan and Quadri, 2012). Another approach is concerned with the integration of BI-based business processes. According to this approach, BI is considered as a mechanism to bridge the gap between business process management and business strategy. Besides all tools available in traditional BI, tools as business performance management (BPM), business activity monitoring (BAM), service-oriented architecture (SOA), automatic decision systems (ADS) and dashboards are included (Golfarelli et al., 2004; Turban et al., 2008; Khan and Quadri, 2012).

Numerous and dispersed studies have been conducted on the identification of BI CSFs in the organisations. Among these efforts, in identifying CSFs of business insight and their applications in BI systems, Moss and Hoberman (2005) have emphasised data modelling and they have referred to three technical, organisational and project aspects. In another study, Yeoh (2011) discussed the CSFs influencing the implementation of BI systems. In their study, Yoon et al. (2017) found that individual intention to adopt a BI application was positively influenced by their motivation to learn the BI application. Taking a global perspective, Jahantigh et al. (2016) designed a set of performance criteria of BI and before them, the researchers had conducted studies aimed to justify and demonstrate the need for BI investments and value. These factors are culture, technical knowledge, accountability, organisational structure, business environment, practices, resistance to change, power and policy, technology, etc. Rajab and Sharma (2017) also presented a survey of the application-based research on neuro-fuzzy systems (NFS) in business on account of the research articles published in various reputed international journals and conferences during the last decade (2005–2014). In a study using ANP approach and identified experts' CSFs, Lin et al. (2009) have developed a model to evaluate the performance of a single BI system, which is used to assess the performance and effectiveness of BI systems and service organisations but they again studied BI independent of the organisational system. Alpar et al. (2015) have stressed software infrastructure as BI CSFs. Hardware and software maturity has been highlighted in other studies as well. Mathew (2012) also examined BI systems adoption in two Indian retail organisations belonging to two different segments. Brooks et al. (2015) provided a framework for a BI maturity model to be used in the healthcare sector.

Generally, in the IT environment, the deployment of any software system requires proper infrastructure by which it can be expected that the efforts will produce the desired result. Evaluation of BI implementation infrastructures also requires identifying operational indicators that can measure the desired infrastructure and it is revealed to what extent the organisation is ready to implement such systems. Literature review on BI suggests an overall classification in defining this concept. This classification is summarised in two managerial and technical approaches with two different paradigms (Table 1).

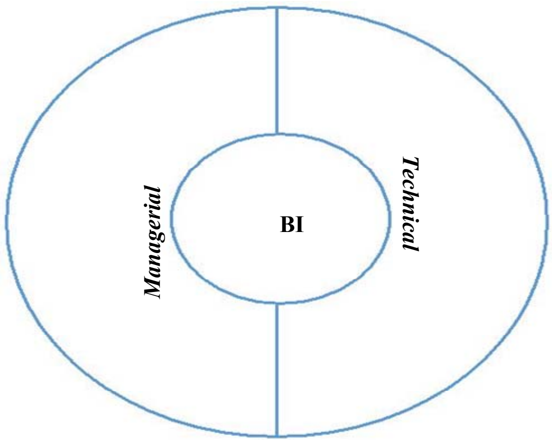
Table 1 Dimensions of BI infrastructure

Indicators	*Dimension*
Suitable hardware platform	*Technical*
• Enabling application communications by organisation's internal network • Suitable hardware for running software available on the organisation • Suitable hardware for data integration software • Suitable hardware for large integrated databases	
Suitable software platform	
• Data storage in databases • Data storage in spreadsheet files • Suitable software for communicating different applications • Automated operational data collection systems	
Senior management support	*Managerial*
• Management's need for quantifiable measures of organisational trend • Accurate and comprehensive reports as senior management's decision-making tools • Senior management's belief in accurate data to achieve strategic objectives • Senior management's belief in automatic data flow	
Necessity of data transparency	
• Managers' belief in data transparency for better decision-making • A multifaceted view of corporate data • Accurate data for comparing plan and performance • Managers tendency to share available data with other units in their affiliated units	
Data generation processes	
• Organisational processes in queuing unit for generating massive data • Organisational processes in the staff unit for generating massive data • Organisational processes for generated data flow • Applying data generated by different processes	
Standards for process integration	
• Inter-organisational communications for process integration • Standards such as ISO for organising and documentation of organisational processes • The similar definitions of common concepts in the organisation • Definition of organisational access levels for gaining access to integrated data	
Familiarity with IT	
• Experience of software application • Familiarity with basic IT skills • Tendency to enhance IT skills • IT training courses	

From the technical viewpoint, BI is viewed as a broad category of tools, software, solutions, and technologies that enable decision-makers to find, accumulate, organise, and access a wider range of information from disparate data sources (Moss and Hoberman, 2004). The technical approach to BI is often focused on the applications and

technologies required for data gathering, storage, analysing and providing affordable access to data to help management make better decisions (Moss and Atre, 2003; Brooks et al., 2015). Managerial approach sees BI as a process in which data is gathered and integrated within and outside the organisation so that they provide relevant information about the decision-making processes. The technical approach considers BI as a set of tools that supports these processes. This approach does not focus on the process itself, but on the technologies, algorithms and tools that enable data storage, recovery, aggregation and analysis (Bose, 2009; Petrini and Pozzebon, 2009). In managerial approach, data from both internal and external sources are integrated to create actionable information for enhanced decision support, and to realise the advantages of the establishment of integrated transaction processing systems and enterprise applications (Whitehorn and Whitehorn, 1999; Moss and Hoberman, 2005; Oracle, 2007).

Figure 1 Main dimensions of BI (see online version for colours)



Therefore, according to the previous studies and specialised interviews with BI managers in the organisations, it is revealed that the establishment of BI system requires suitable managerial and technical platforms (Figure 1). These two approaches are intertwined and cannot be considered entirely independent factors. The managerial approach can influence the technical approach from two perspectives:

1 managerial supports from financing the hardware facilities

2 managerial supports from developing applications by which information can be gathered automatically.

In technical approach, suitable hardware and software platforms have been emphasised. In managerial approach, senior management's support, managers' familiarity with BI, the need for data transparency, data generation processes, and data integration processes are also emphasised as main managerial infrastructures.

3 Method

This study is a pure research, which aims to identify the technical and managerial infrastructures of BI for large and medium-sized companies. The literature review, specialised structured and semi-structured interviews, and questionnaire have been used for data collection. The population of the study consists of senior IT executives and managers in Iranian large and medium-sized organisations. The study data have been collected during a five-year period.

In this study, since confirmatory factor analysis (CFA) technique has been used, some observations are intended for the sampling. In fact if it is not proven that the items (observable variables) have measured the latent variables properly, the relationships may not be tested (Kline, 2011). It is very important to determine the minimum sample size required for data collection related to the structural equation modelling (SEM). Although there is no general agreement about sample size required for factor analysis and structural models (Schreiber et al., 2006), according to many researchers, the minimum required sample size is 200 (Hoelter, 1983; Garver and Mentzer, 1999; Sivo et al., 2006; Hoe, 2008). In CFA, the minimum sample size is determined based on factors not variables. If SEM is used, about 20 samples are necessary for each factor (latent variable). The recommended sample size for CFA is about 200 samples for ten factors (Kline, 2011). Therefore, in this study, a sample of 400 subjects has been used. Six questionnaires could not be used, and ultimately, data has been extracted from a sample of 394 subjects.

For providing the measurement scale of BI infrastructure, first, the main dimensions of BI have been identified based on relevant literature and interviews with academic and practical experts and scholars. Then, a set of items has been identified for each dimension.

Content validity, construct validity and convergent validity have been used to examine the scale validity. The Cronbach's alpha and reliability composite are also calculated to assess the reliability. Multivariate analysis is one of the strongest and best methods of analysis in the field studies. The obtained data are also analysed using LISREL software.

4 Data analysis

In this study, two scales are used to measure BI infrastructure. CFA is used for the validation of the items of technical and managerial infrastructure scales. The second order CFA includes measurement model and path model. The measurement model represents the relationship between items (observable variables) and constructs (latent variables). The path model also represents the relationship between main construct and secondary constructs.

In CFA and SEM, several points are of great importance; the power of relationship between variables is represented by loading factor. The loading factor is between zero and one. Generally, if the loading factor is less than 0.3, the relationship is weak and it is ignored. The factor loading between 0.3 and 0.6 is acceptable and if it is higher than 0.6, it is very favourable. When the correlation between variables was identified, a significance test should be done. However, t-value statistic is used to determine the

significance of the factor loading. At 5% confidence level, if t-value is higher than 1.96, the factor loading is significant (Foster et al., 2006; Kline, 2011)

Table 2 CFA of BI technical infrastructure scale

1	*Technical dimension*		*Factor load*	*t-value*	*AVE*	*CR*	*Cronbach's α*
SHP	*1-1*	*Suitable hardware platform*			*0.546*	*0.825*	*0.774*
SHP1		Enabling application communications by organisation's internal network	0.84	10.81			
SHP2		Suitable hardware for running software available on the organisation	0.63	9.27			
SHP3		Suitable hardware for data integration software	0.64	8.72			
SHP4		Suitable hardware for large integrated databases	0.82	11.16			
SSP	*1-2*	*Suitable software platform*			*0.597*	*0.855*	*0.783*
SSP1		Data storage in databases	0.88	14.44			
SSP2		Data storage in spreadsheet files	0.77	12.43			
SSP3		Suitable software for communicating different applications	0.72	6.15			
SSP4		Automated operational data collection systems	0.71	7.48			

Table 2 shows the CFA results of BI technical infrastructure indicators. The CFA results of BI managerial infrastructure indicators are also shown in Table 3.

Table 3 CFA of BI managerial infrastructure scale

2	*Managerial dimensions*		*Factor load*	*t-value*	*AVE*	*CR*	*Cronbach's α*
SMS	*2-1*	*Senior management support*			*0.509*	*0.804*	*0.854*
SMS1		Management's need for quantifiable measures of organisational trend	0.68	7.88			
SMS2		Accurate and comprehensive reports as senior management's decision-making tools	0.77	9.19			
SMS3		Senior management's belief in accurate data to achieve strategic objectives	0.78	9.53			
SMS4		Senior management's belief in automatic data flow	0.61	7.09			

Table 3 CFA of BI managerial infrastructure scale (continued)

2	*Managerial dimensions*		*Factor load*	*t-value*	*AVE*	*CR*	*Cronbach's α*
NDT	*2-2*	*Necessity of data transparency*			*0.610*	*0.862*	*0.731*
NDT1		Managers' belief in data transparency for better decision-making	0.71	9.88			
NDT2		A multifaceted view of corporate data	0.83	11.31			
NDT3		Accurate data for comparing plan and performance	0.80	11.60			
NDT4		Managers' tendency to share available data with other units in their affiliated units	0.78	10.57			
DGP	*2-3*	*Data generation processes*			*0.502*	*0.800*	*0.769*
DGP1		Organisational processes in queuing unit for generating massive data	0.82	11.09			
DGP2		Organisational processes in the staff unit for generating massive data	0.62	7.46			
DGP3		Organisational processes for generated data flow	0.68	9.05			
DGP4		Applying data generated by different processes	0.70	8.74			
SPI	*2-4*	*Standards for process integration*			*0.687*	*0.897*	*0.812*
SPI1		Inter-organisational communications for process integration	0.77	11.33			
SPI2		Standards such as ISO for organising and documentation of organisational processes	0.86	13.45			
SPI3		The similar definitions of common concepts in the organisation	0.89	14.35			
SPI4		Definition of organisational access levels for gaining access to integrated data	0.89	14.25			
FIT	*2-5*	*Familiarity with IT*			*0.649*	*0.880*	*0.744*
FIT1		Experience of software application	0.82	11.95			
FIT2		Familiarity with basic IT skills	0.84	13.01			
FIT3		Tendency to enhance IT skills	0.68	8.88			
FIT4		IT training courses	0.87	12.75			

Figure 2 CFA of BI technical infrastructure scale

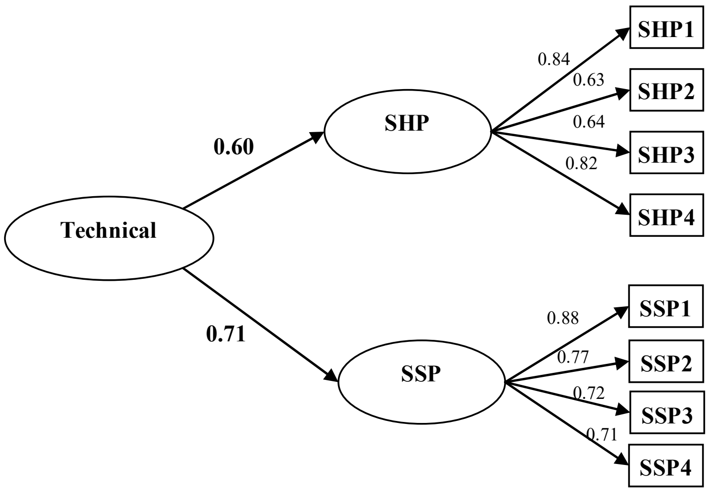
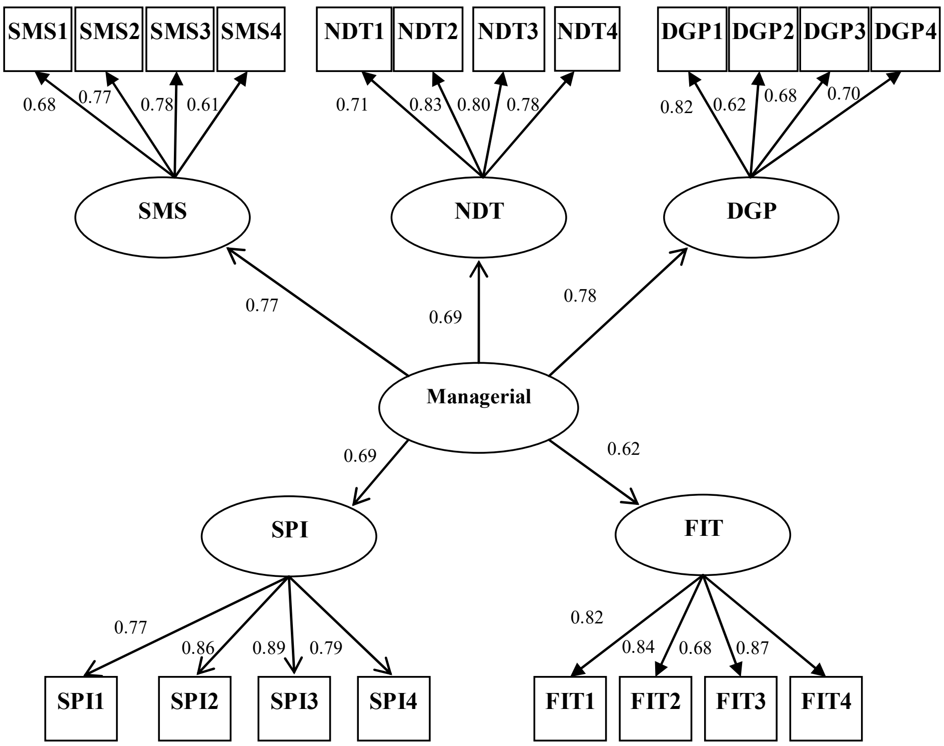


Figure 3 CFA of BI technical infrastructure scale



If one or more attributes are measured, the correlation between these measurements provides two main validity indices. If the correlation between factor loadings is high, the questionnaire has convergent validity. The average variance extracted (AVE) and composite reliability (CR) should be calculated for convergent validity. There is

convergent validity when the following equation is established (Fornell and Larcker 1981):

$$\begin{cases} CR > 0.7 \\ CR > AVE \\ AVE > 0.5 \end{cases}$$

As shown in Table 2 and Table 3, AVE in all cases is greater than 0.5 and CR is also greater than 0.7. In all cases, CR is also greater than AVE (CR > AVE).

Goodness of fit is also one of the most important issues of SEM and CFA. There are indices that determine whether the overall model has good fit or not. Two main indices have been used for model's fit. Normalised chi-square ($\chi 2$/df) is another common index for considering free parameters in calculating the fit indices. It is calculated by chi-square ($\chi 2$) dividend by degree of freedom (df). If $\chi 2/df < 2$, it is optimal. In CFA and SEM, RMSEA is also used as one of main fit indices. If RMSEA < 0.05, it is optimal. Some other indices including GFI, CFI, NFI, and NNFI should be greater than 0.9 (Schumacker and Richard, 2004).

For technical scale and managerial scale, $\chi 2$/df is 1.26 and 1.46, respectively. RMSEA is 0.026 for technical scale and 0.034 for managerial scale. Some other fit indices have also been used to fit the model, which are shown in Table 4. Other fit indices are also acceptable.

Table 4 Fit indices of structural model of main hypothesis

Fit index	*χ2/df*	*RMSEA*	*RMR*	*GFI*	*AGFI*	*NFI*	*NNFI*	*IFI*
Acceptable values	1 – 5	< 0.05	< 0.05	> 0.9	> 0.9	> 0.9	> 0.9	0 – 1
Results of technical scale	1.26	0.026	0.014	1.00	0.97	0.99	1.00	1.00
Results of managerial scale	1.46	0.034	0.034	0.95	0.92	0.96	0.98	0.99

It should be noted that CFA has been saturated in multiple steps. Hence, the fit indices are acceptable. Saturation is a process by which unexplained error variances are linked together that are likely affected by a common factor outside of the model. By identifying the same causal root between items, which are not embedded in the model, the final model is improved. This model improvement can be observed with more optimised fit indices. In the saturated model, the coefficients and factor loadings between variables are also improved and become closer to the true values.

In this model, the factor loadings of technical and managerial scales have also been calculated. The factor loadings of the relationship between each one of technical and managerial scales and its own construct are above 0.6. Furthermore, in all cases, t-value is greater than 1.96 indicating these dimensions have been selected properly for the assessment of technical and managerial preparation and the model is supported.

5 Conclusions

Several studies have been done on BI in academia. On the other hand, organisations have also invested heavily in BI. However, it seems that BI has taken two separate paths theoretically and practically. Most academic studies have described BI and the

advantages of applying it and little scientific solution has been suggested for BI implementation. Organisations have also more emphasised the cost-benefit analysis and consulting with companies providing the BI software. In this study, the gap between theory and practice was bridged. In other words, consistent with the principles of scientific method, an operational scale was presented for BI implementation.

Executives should not act hastily for applying BI and they do not consider it as a panacea for all problems. Before the establishment of BI in the organisation, its infrastructure must be examined properly. For the feasibility of BI implementation, the organisation's infrastructure should be explored technically and managerially. Like any other organisational projects, 'the senior management support' is the first and most important prerequisite for the successful BI implementation. Two factors determining the degree of management support from the BI project are 'managers' familiarity with IT' and 'the need for information transparency'.

Organisations that have already been applied the process standardisation trends can be leaders in BI implementation. One of these procedures is ISO standards in the organisation. One of main infrastructures before the establishment of BI in the organisation is documentation, generating and storing large volumes of data. Data should be collected from different parts of the organisation and stored in the data storage files such as excel spreadsheets and the access simple database, etc. This requires the same definition of the common concepts in the organisation. The next issue is data sovereignty in the organisation, i.e., data access levels are defined and it is determined that each person may access what level of data.

The main achievement of this study was to provide a valid and reliable scale for measuring BI infrastructure in the organisations. The findings indicated that existing hardware platform should allow the organisation to provide application communications via the internal network. There should be also suitable hardware to run existing applications such as data integration software in the organisation. In such cases, it could be expected to implement BI during a short period and with low costs, and the investment risk would be low.

5.1 Suggestions and limitations

This was one of the first studies evaluating BI CSFs based on the scientific research. Therefore, the research trend and indices might have some shortcomings. Using qualitative research methods and specialised interviews for developing scales could be useful in improving the results and model. This study investigated just Iranian medium and large-sized organisations, which was itself another limitation for the researchers. For developing a global scale, the existing model could be tested in other countries.

An essential suggestion to the future researchers is to explore BI CSFs. The authors believe that the development of the existing scale was not only an ultimate goal. A major gap between academic researches on BI is that an independent investigation has not been done on BI CSFs, while CSFs are a very important issue for industries and managers.

Organisational managers are also recommended to assess BI infrastructure based on the proposed scale before implementing and establishing it in their organisations. BI establishment requires substantial investment that is cost-effective considering the benefits of BI. However, the failure rate of these projects is very high. Therefore, apart from relying on the opinions of the experts providing BI software package, the organisational infrastructure should also be assessed.

In summary, it could be said that a BI project, like any other project, has three basic steps: infrastructure assessment, BI implementation, and BI performance measurement. In this study, BI CSFs were measured. For implementation, extensive studies could be conducted on BI CSFs. The technology assessment models (TAMs) and balanced scorecard (BSC) approach would be used for BI performance measurement.

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